Nat Hazards (2015) 75:1883–1908
DOI 10.1007/s11069-014-1402-2

ORIGINAL PAPER

Mapping composite vulnerability to groundwater arsenic contamination: an analytical framework and a case study in India

Sushant K. Singh · Neeraj Vedwan

Received: 28 November 2013 / Accepted: 25 August 2014 / Published online: 3 September 2014

Abstract Groundwater arsenic (*As*) contamination affects millions of people in South Asia. In this paper, we propose a composite vulnerability framework to identify, for mitigation, the population who are at the highest risk of suffering adverse impacts from exposure to *As* and warrant mitigation measures. Bihar, India, which was selected for the case study, has large areas with *As* concentrations far exceeding the upper limits of acceptable level of *As* in drinking water. Drawing on the existing social science research, we identify a host of socioeconomic and demographic variables, in addition to *As* concentration in groundwater, which compound a community's vulnerability to the adverse effects of *As*. The result is a "composite vulnerability index," which consists of biophysical, socioeconomic, and demographic factors that collectively determine a community's overall vulnerability to *As*. Additionally, using geographic information systems (GIS), we represent the composite vulnerability index visually through a set of maps, which highlight the interaction between different community characteristics to generate unique community vulnerability profiles. In summary, this paper outlines a systematic approach to understanding vulnerability to groundwater *As*, as both social and natural construct, which can be applied to different geographic areas, and to improving decision making and planning pertaining to diverse environmental problems.

Keywords Vulnerability · Arsenic · Socioeconomic–demographic · Biophysical environment · Policy · Decision making

S. K. Singh (✉)
Department of Earth and Environmental Studies, Montclair State University, Montclair, NJ 07043, USA
e-mail: sushantorama@gmail.com; singhs10@mail.montclair.edu

N. Vedwan
Department of Anthropology, Dickson Hall-141, Montclair State University, Montclair, NJ 07043, USA
e-mail: vedwann@mail.montclair.edu

1 Introduction

1.1 Arsenic contamination: a naturally occurring hazard

Groundwater arsenic (*As*) contamination is a global phenomenon affecting more than 70 countries on six continents (Ravenscroft et al. 2011). As a densely populated region, the Ganga–Meghna–Brahmaputra (GMB) plain intensively exploits groundwater resources, experiencing a myriad of environmental impacts associated with local, regional, and global issues. The vulnerability of GMB is enhanced due to threats from natural processes, and socioeconomic and demographic forces. The GMB plain in India and Bangladesh contains the highest *As*-contaminated contiguous area in South Asia (SA) affecting about 500 million people's lives and encompasses an area of 569,749 km^2 (Hossain et al. 2006). The groundwater *As* contamination in India was first noticed in 1976 in the Chandigarh district, about eight decades after the first case of *As* poisoning in Poland (1898) (Mandal and Suzuki 2002). Later in 1982, India received a wake-up call because of another case of *As* poisoning in North 24 Pargana district of the state of West Bengal (WB) (Chakraborti et al. 2003). The groundwater's *As* contamination and its health impact on human beings has been extensively studied in WB (Chowdhury et al. 2000; Mazumder et al. 2010; Guha Mazumder and Dasgupta 2011; Rahman et al. 2013). A total of 111 community blocks (out of 341) have been reported as *As*-affected blocks in 12 *As*-affected districts (out of 19) (SOES 2006). About two decades after the WB case, very high concentrations of *As* were detected in the groundwater in Bihar (Chakraborti et al. 2003). Later, the groundwater *As* contamination was revealed in other geographic locations in India including Uttar Pradesh, Jharkhand, Assam, Tripura Arunachal Pradesh, Nagaland, Manipur, Punjab, Haryana, Himachal Pradesh, Chhattisgarh, Hyderabad, and Andhra Pradesh (Datta and Kaul 1976; Mukherjee et al. 2006; Nickson et al. 2007). *As* is a group "A" carcinogen, and the ill effects of exposure to it cause serious health problems among the affected groups, which can lead to their economic and social marginalization. Reducing the risk from hazards of natural origin (arsenic in this case) is a major challenge concerning global environment change (Birkmann et al. 2013). Groundwater *As* contamination is most appropriately considered a chronic hazard because of its long-term, cumulative harmful effects. A chronic hazard presents unique challenges in terms of the public perception, which may engender and influence subsequent policy responses.

1.2 Vulnerability: perspectives, indexes, and models

Vulnerability assessment of natural hazards and climate change has emerged in the past decades as an important research field bringing together scientists from different disciplines (Adger et al. 2004; IPCC 2007; Parry 2007; Birkmann et al. 2013). In the absence of a universal definition for vulnerability and common conceptualization, formulations of vulnerability have proliferated (Birkmann et al. 2013). The natural science research communities often focus on the quantification of different factors contributing to vulnerability, often to the exclusion of socioeconomic factors. These approaches highlight physical vulnerability and often attempt to quantify damage ranges. These are illustrated using vulnerability curves, which help determine acceptable levels of potential losses (Kienberger et al. 2009; Papathoma-Köhle et al. 2011). In contrast, social science approaches often encompass a broad focus and examine, in particular, the impact of exposure to environmental hazards on individual households or a community, as well as the contextual conditions that influence social vulnerability (Wisner 2004). According to

Phillips and Fordham (2009), social vulnerability to natural hazards is driven by social inequality and is deeply embedded in social structures that are often resistant to change (Phillips and Fordham 2009). Many assessment approaches characterize vulnerability according to the degree of susceptibility or fragility of communities, systems, or elements at risk and their capacity to cope under adverse conditions. In recent years, different frameworks have been developed to better systematize different facets of vulnerability, most often in relation to climate change adaptation and disaster risk management (Birkmann et al. 2013). However, developing a universal metric or measurement tool for vulnerability assessments across all disciplines is challenging because of the definitional elusiveness and heterogeneous nature and scale of analysis (temporal and spatial). The vulnerability indexes or indicators are quantifiable measures envisioned to represent a characteristic or a parameter of a system of interest using a single value, and have been applied in different contexts using different variables (Cutter et al. 2008). Among all the variables used to derive vulnerability indicators, socioeconomic status (wealth or poverty), age, special needs population, gender, race, and ethnicity have been studied most extensively as social factors that increase or decrease the impact of specific natural hazard events on a local population (Tierney 2001; Tierney et al. 2001; Center 2002; Bates and Swan 2007). It has been reported that selecting a single variable (e.g., race, gender, or poverty) does not adequately capture the characteristics of the communities described. In most cases, it is a combination of several socioeconomic attributes and circumstances, which defines social burdens from natural hazards (Cutter et al. 2009).

The choice of methodology to derive vulnerability indicators and appropriate weighting for each individual variable has been the most important constraint in vulnerability studies. Because of the absence of reliable theoretical and/or statistical evidence needed to assign weights, all indicators are usually assigned equal weight, thereby according them the same relative importance (Cutter et al. 2009). However, indicators can also be weighted according to the percent variance explained by each factor (Cox et al. 2006). Furthermore, vulnerability maps can be invaluable for adapting and planning mitigation frameworks in highly vulnerable areas. For the current study, we define vulnerability as the risk of experiencing economic loss, health problems, social isolation, social discrimination, loss of opportunities, or decline in socioeconomic status during the period of exposure to specific or multiple socioeconomic or environmental problems. No previous studies have been reported, which have applied the vulnerability framework to *As* contamination. This study is the first of its kind to propose a conceptual composite vulnerability framework and derive composite vulnerability indexes for *As* contamination.

2 Framework and methodology

2.1 Composite vulnerability framework

Deriving and mapping composite vulnerability (CV) to *As* contamination is a key step in quantifying total vulnerability due to existing biophysical and socioeconomic conditions in *As*-contaminated areas. The CV map has the potential to predict highly vulnerable areas where *As* mitigation is an urgent necessity; type(s) of *As*-mitigation technology(s) requires feasibility, sustainability for the specific vulnerable area(s); and the area(s) where the likelihood of success of an *As*-mitigation program is greatest. The components of CV framework are based on the concept that vulnerability is a function of *exposure, sensitivity, and adaptive capacity* (Fig. 1). The definitions of these three elements of vulnerability

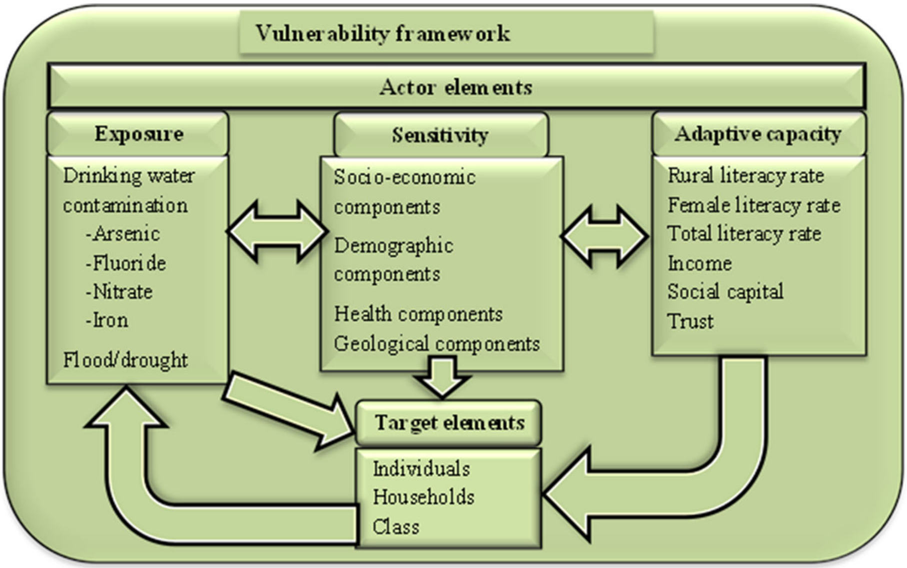

Fig. 1 Conceptual model of composite vulnerability framework

assessment have been adapted for our work. *Exposure* can be defined as the degree of environmental stress upon a particular unit of analysis; it may be represented as either long-term change in environmental conditions or changes in the magnitude and frequency of extreme events. *Sensitivity* is the degree to which a system will respond to a change in the environment, either positively or negatively. *Adaptive capacity* is the ability of a system to adjust to actual or expected environmental stresses, or to cope with the consequences. *Adaptive capacity* is also considered "a function of wealth, technology, education, information, skills, infrastructure, access to resources, and stability and management capabilities" (UNEP 2003). Although, theoretically, technology plays a vital role in enhancing societal adaptive capacity, we have omitted technology as a variable from our study because groundwater *As* contamination mainly affects rural areas in SA, where technological development has been minimal (Das 1999; Singh and Jha 2012).

2.1.1 *Quantifying vulnerability indexes*

The method to derive vulnerability indexes was modified and simplified for this study. The core of the methodology is the method used to derive vulnerability indexes in the guidelines of the United Nations Environment Program's Assessing Human Vulnerability to Environmental Change (2003). Data were treated as per the UNEP guidelines (UNEP 2003). The variables used to derive vulnerability indexes are listed in Table 1.

The steps involved in quantifying vulnerability indexes are deriving vulnerability interval value (VIV) and vulnerability indexes (VI). The VIV is derived by using Eq. (1).

$$\text{Vulnerability Interval Value (VIV)} = \frac{\mathrm{VV}_{\max} - \mathrm{VV}_{\min}}{\mathrm{VI}_{\max}} \quad (1)$$

where $\mathrm{VV}_{\max}$ is the maximum value of vulnerability variable; $\mathrm{VV}_{\min}$ is the minimum value of vulnerability variable; and $\mathrm{VI}_{\max}$ is the maximum value of vulnerability index at "5

Table 1 Indicator variables for vulnerability calculation

Exposure	Sensitivity	Adaptive capacity
Arsenic contamination	Rural population (RP)	Total literacy rate
Fluoride contamination	Population below the poverty line (BPL)	Female literacy rate
Nitrate contamination	Scheduled caste population (SC)	
Iron contamination	Scheduled tribe population (ST)	
Flood incidence	Population growth rate (PGR)	
Drought incidence	Population density (PD)	
	Infant mortality rates (IMR)	
	Kala-azar prevalence	
	TB incidence	
	HIV prevalence	
	Geological formation	
	Lithology	
	Physiography	

levels" of vulnerability scale. After deriving the VIV, the VIs can be calculated based on Eq. (2)

$$\mathrm{VI}_{\mathrm{ndex}} = \mathrm{VV}_{\min} + \mathrm{VIV} \tag{2}$$

where $\mathrm{VV}_{\min}$ is the minimum value of vulnerability variables and VIV is the vulnerability interval value derived from the Eq. (1).

Furthermore, following these steps, five vulnerability indexes were derived and at every consecutive step, $\mathrm{VV}_{\min}$ was replaced with VI value of the previous step. Finally, five levels of vulnerability indexes were derived and given appropriate weightage (weighted equally), and each As-affected district was assigned an appropriate VI values (Table 2).

The VI values for *As*-contaminated areas were derived based on the *As*-concentration profile of the area. The VI values from 1 to 5 were assigned based on *As* concentration in the drinking water between 0–10 μg/L, 11–50 μg/L, 51–100 μg/L, 101–200 μg/L, and *As* levels more than 200 μg/L, respectively. In the absence of fluoride (*F*), nitrate (*N*), and iron (*Fe*) concentration data, areas with these contaminants were given the VI value "1" for each contaminant and the area without these contaminations the VI value "0." Areas affected with flood and droughts were treated similarly to *F*-contaminated areas. We did not characterize flood- or drought-affected areas according to the intensity of their occurrence. Flood and drought in the region are chronic natural hazards and affect a largely impoverished population, often resulting in mass displacement and loss of livelihoods. The damage is significant, and evaluating flood or drought intensity based on their occurrence and impacts in more than half of the districts in the state is beyond the scope of our work, and even more importantly, unlikely to yield additional insights. Therefore, we only considered the presence or absence of flood or drought in the *As*-affected areas as an additional environmental stressor. Hydrogeochemical conditions also significantly contribute to the sensitivity of *As*-prone areas. For example, the following characteristics of the area such as geological formation, lithology, physiography, high HCO_3^- load in the groundwater have been correlated with the *As* concentration in affected areas (Lado et al. 2008; Winkel et al. 2008; Saha and Shukla 2013). Hydrogeochemical parameters such as hydraulic conductivity and chemical composition are aquifer-specific and could be used to predict *As* vulnerable areas (Lado et al. 2008, Winkel et al. 2008). For this study, we have used information about the geological formation (Quaternary to upper quaternary = 1 and Quaternary = 2), lithology of the areas (younger alluvial, older alluvial, and red sandy

Table 2 Vulnerability indexes and associated vulnerability category

Vulnerability indexes	Vulnerability
VI-1	Resilient
VI-2	At risk
VI-3	Less vulnerable
VI-4	Moderately vulnerable
VI-5	Highly vulnerable

soil = 1; younger alluvial and older alluvial soil = 2; younger alluvial and calcareous alluvial soil = 3; and younger alluvial soil = 4), and the physiography (hill = 1; alluvial plain = 2) of the areas.

2.2 Principal component analysis (PCA)

Principal component analysis (PCA) has been widely used in vulnerability studies (Cutter and Finch 2008; Schmidtlein et al. 2008; Guillard-Gonçalves et al. 2014). PCA provides an opportunity to reduce the dimensionality of the multivariate data sets (Warner 2012). In large data sets with several variables, some of the variables may be positively or negatively correlated. For instance, some of the variables essentially contain the same information as the twenty-one vulnerability indicators that were used to derive composite vulnerability indexes in this study (Warner 2012). Therefore, PCA finds a new orthogonal coordinate system of uncorrelated predictors to represent the original vulnerability indexes data (Warner 2012). PCA was performed on the data used to derive vulnerability indexes in this study using the Statistical Package for the Social Sciences (SPSS) version 21 (SPSS 2012). Each component in PCA is a linear combination of the original variables used to derive vulnerability indexes (Warner 2012). The first principal component is in the direction of greatest variance in the original data set (Warner 2012). PCA produces eigenvalue and loading, which are, respectively, a sum of the squared loadings on a component and explain how strongly a variable is correlated with the component (Warner 2012). Loading of vulnerability indicators close to ± 1 and greater than .5 was considered significant (Warner 2012). A correlation matrix between all the variables was derived to see the association between all the possible variables. PCA was performed with varimax rotation to obtain easily interpretable component loadings, and the components with eigenvalues greater than 1 were extracted (Warner 2012). A communalities test was also performed to see that how much of the variance in each of the original variables is explained by the extracted components (Warner 2012). Communalities for variables greater than 50 % were desired. A scree plot was also derived, which is a graphical presentation of the eigenvalues across the number of components (Warner 2012). Furthermore, the extracted components were named based on the higher loadings of the vulnerability indicators (Warner 2012). Since the number of indicators of *exposure, sensitivity,* and *adaptive capacity* were heterogeneous, we derived a ratio to name each component applying the following equation:

$$\text{Ratio to name the principal components (RNPC)} = \frac{\text{Total number of indicators with high loadings } (> 0.40)}{\text{Total number of indicators in the data set}}$$

Therefore, the components were named based on the highest RNPC values close to “1.”

2.3 The case study of Bihar state: a real-world case of a multi-stressor environment

2.3.1 Biophysical environment of the study area

Bihar, located in the GMB basin, is one of the worst *As*-affected states of India, sharing its geographic boundary with Bangladesh, West Bengal, and Nepal—three of the most *As*-affected vicinities of SA (Saha 2009). *As* contamination in the groundwater of Bihar is a phenomenon only recently discovered; it was first investigated in 2002 in the Semaria Ojha Patti village of the Shahpur block of the Bhojpur district (Chakraborti et al. 2003). The state still follows the old standard of 50 μg/L set for *As* in drinking water established by the World Health Organization (WHO 2004). Although the acceptable limit for *As* in drinking water is 10 μg/L, set by the Bureau of Indian Standards (BIS), however, in the absence of alternative sources, 50 μg/L of *As* is acceptable (BIS 2012). So far, out of a total of 82,000 groundwater samples tested for *As* contamination in 15 districts (of the total of 37 districts) of Bihar, 11 % exceed 50 μg/L, covering 57 community blocks in fifteen districts (Saha 2009). The concentrations of naturally occurring *As* in groundwater in Bihar (>1,000 μg/L) exceeded several times the *As* levels reported in groundwater in many countries such as Chile, Brazil, Mexico, Germany, Hungary, United Kingdom, and USA (Nordstrom 2002, Ghosh et al. 2005, 2007, 2008; Saha et al. 2009).

The spatial distribution of groundwater *As* in Bihar is irregular, and contamination occurs in patches. The hot spots (>50 μg/L) have been found to be confined within the Holocene newer alluvium of the thick multi-cyclic sand, clay, sandy clay, and silty clay sequence of a depth within 50 m below ground level, jeopardizing the hand pump-based rural drinking water supply in the state (Saha et al. 2009). The Pleistocene older alluvium was usually free from *As* contamination. Additionally, a high positive correlation between *As* and iron contamination has been found in the state, doubling the cost of filtration, and operation and maintenance of filtration equipment due to multiple metal contamination (Saha et al. 2010). Furthermore, the elevated *As* load is confined to the flood plain where rainfall facilitates percolation of organic carbon to the groundwater, which stimulates microbial respiration, triggering a reductive dissolution of *As* and iron in the solid phase (Mukherjee et al. 2012). These hydrogeochemical phenomena produce HCO_3^- in shallow groundwater that helps mobilization of *As* in the groundwater (Saha et al. 2010). Geochemical analysis of *As*-contaminated groundwater in Bihar reveals that the contaminated groundwater was found to be near neutral to mildly acidic and dominated by alkaline earth (Ca^{2+} and Mg^{2+}) and weak acid (HCO_3^-) (Saha et al. 2008, 2010, 2011). The presence of high concentrations of HCO_3^- in groundwater significantly contributes to the hydrogeochemical evolution of groundwater and trace metal mobilization in the area (Saha 2009). In a recent study, Saha and Shukla (2013) have explained that the *As*-contaminated groundwater in the state is primarily evidenced by three hydrogeochemical facies dominated by Mg and HCO_3 (Fig. 2). The influence of redox conditions on *As* mobility in the groundwater has been widely reported in the literature (Ravenscroft et al. 2011). A mixed correlation between pH and *As* concentrations has been reported in the state (Singh et al. 2014). There are studies investigating the association between the depths of the tested hand pumps and the concentrations of *As* in groundwater in the state. However, none of them found any significant correlation between the two parameters (Saha and Shukla 2013; Singh et al. 2014).

Although the state has rich groundwater, the fact is that shallow aquifers, on which the rural water supply is heavily dependent, are contaminated with *As*, and this situation makes it difficult to provide potable water in the affected areas (Saha and Shukla 2013). The state is endowed with 36 % replenishable groundwater resource for further extraction. The

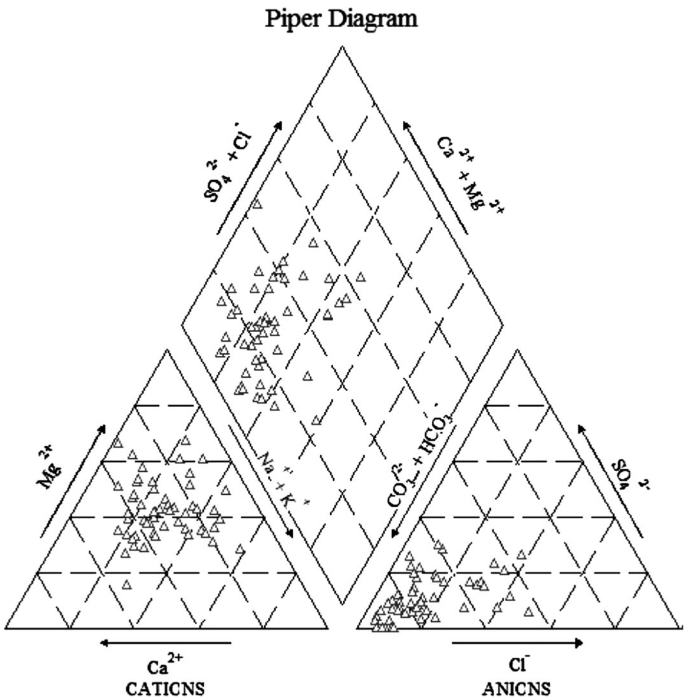

Fig. 2 Piper diagram showing different hydrogeochemical facies of *As*-contaminated groundwater in Bihar (*Source*: Saha and Shukla 2013)

transmissivity of the aquifer (3,718 and 6,986 m^2/day) indicates its higher potentiality than the aquifers in *As*-affected areas in WB (300–8,800 m^2/day); hydraulic conductivity of the groundwater ranges from 64.88 to 82.00 m, indicating very good aquifer potential; and the deeper aquifer is protected by a middle clay, which may be developed for community drinking water supply by deep tube wells having a yield capacity of 150 m^3/h (Saha et al. 2011). This hydrogeochemical information is valuable and could help creating mitigation strategies. However, further investigation in all the *As*-contaminated areas is warranted.

A toxic risk index ranging from .9 to 192.50 has also been derived in the state, exceeding the lower and upper end of the ranges of the typical toxic risk index 1.00, suggesting that the residents in the area might confront seriously adverse toxic health impacts (Singh and Ghosh 2012, Singh et al. 2014). The exposed communities were found to be consuming up to 1,469 μg/day of *As* against the maximum allowable limit of 200 μg/day through *As*-contaminated water and food materials (rice, wheat, maize, and lentils) in the state. Therefore, the cumulative effect is making children (57/1,000) susceptible to cancer with an average prevalence of skin pigmentation of 1.35 (Singh and Ghosh 2012, Singh et al. 2014). In a recent study, consumption of *As* in excess of 200 μg/kg through cooked rice in India has been linked with elevated genotoxic effect in human beings (Banerjee et al. 2013). A series of obstetric outcomes were also documented in women exposed to *As*-contaminated groundwater, and sixty persons with Arsenical skin lesions were reported in Bihar (Chakraborti et al. 2003). The *As* contamination zone is confined to the socioeconomically deprived communities of the state living along the river Ganges, making the exposed population (more than 8 million) highly vulnerable to its toxic effects (Singh et al. 2014).

2.3.2 Socioeconomic–demographic health conditions of Bihar

Globally, India is home to one of the largest populations of impoverished people, who are highly vulnerable to health problems (Cord et al. 2009). Bihar is the second poorest state in the country, where more than 33 million people currently live below the poverty line, with a monthly per capita income of only Rs. 354.36 (about USD $7.8), and more than 2 million people have little or no food security, resulting in dietary deficiencies that increase susceptibility to Arsenicosis (BRLPS 2007, Census 2013). The state has a total population density of 1,102 person/km^2 and a decadal population growth rate of 28.43 %. The total literacy rate is only 48 %, due to inequitable access to education and a high dropout rate (BRLPS 2007). The impacted communities are largely unaware of the contamination problem because of poor literacy, especially for women whose literacy rate is only 33.53 %. Consequently, women lack equal access to resources; are more likely to be impoverished and illiterate; and are susceptible to abandonment, divorce, ostracism, or domestic violence when afflicted with Arsenicosis (BRLPS 2007; Brinkel et al. 2009). Fear of contamination has affected social ties and resulted in fewer marriages, causing cultural stress between generations (Bihardays 2011). Arsenicosis-affected individuals and communities also face social marginalization, including alienation, stigmatization, and discrimination. A typical community in an *As*-affected rural area is presented in Fig. 3.

Additionally, the high infant mortality rate, kala-azar prevalence, TB incidence, HIV prevalence, frequency of diarrhea, and other diseases significantly contribute to vulnerability of communities. Furthermore, multiple environmental contaminants such as *F*, *N*, and other contaminants, as well as other environmental stresses such as flood and drought

Fig. 3 Typical community in an *As*-affected area in Bihar (Photograph by Sushant Singh 2013)

incidence, in addition to exposure to stressors like climate change or regional biophysical or political issues further amplify vulnerability to *As*.

2.4 Data collection and processing

Arsenic, fluoride, nitrate, and iron contamination data in different districts of Bihar were extracted from the published literature and field survey (SOES 2006; Ghosh et al. 2007, 2008; Saha 2009; Saha et al. 2009; Singh 2011). The at-risk population was calculated based on the number of blocks contaminated with *As*. In this study, we defined the threshold for population at risk at 10 μg/L of groundwater *As* contamination (Nickson et al. 2007). Flood and drought incidence was pooled from federal reports. Socioeconomic, demographic, and health-related data were extracted from the Census-2001 and policy documents. Hydrogeological data were extracted from the published maps and state reports (BSPCB 2007; GSI 2012; BAMETI 2014). All the data were standardized and processed according to the UNEP guidelines (UNEP 2003).

A Shapefile for Bihar with district boundaries and rivers available at the http://www.diva-gis.org/ was downloaded. All the data were incorporated into the attribute table, and maps were created using ArcGIS 10.1 (ESRI 2012).

3 Results and discussion

3.1 Arsenic vulnerability maps (AVM)

The AVM explicates the areas contaminated with *As* ranging from 0 μg/L to >1,000 μg/L of *As* (Fig. 4) and the population at risk due to ready access to the drinking water sources with *As* levels more than 10 μg/L (Fig. 5). Five districts were found to be contaminated with >1,000 μg/L of *As* including Buxar, Bhojpur, Patna, Samastipur, and Bhagalpur. Nine districts were found to have *As* below the BIS standard of 50 μg/L in the state (Fig. 4). A total of about 9 million population was found to be at risk in the state. The population in about one-half of the *As*-affected districts was found to be highly vulnerable to *As* contamination, amounting to a total population of about 4.4 million out of the total at-risk population (Fig. 5). The least at-risk population in the *As*-affected districts was found to be 7 % in Darbhanga district, covering only one block; however, the highest *As*-affected population (63 %) was found in Khagaria district, covering a total of three blocks (Fig. 5).

3.2 Mapping exposure

3.2.1 Mapping environmental vulnerability

Only Bhagalpur district was found to be a highly environmentally vulnerable area. Bhagalpur is a unique *As*-affected area because the groundwater in this area is contaminated with *As, F*, and *N*. Also, the district is affected by flood and drought incidences (Fig. 6). Five districts Bhojpur, Buxar, Patna, Samastipur, and Vaishali were found to be moderately vulnerable, followed by the less vulnerable two districts and four at risk. Only three districts including Darbhanga, Lakhisarai, and Purnia were the resilient districts because of the comparatively less biophysical stressors.

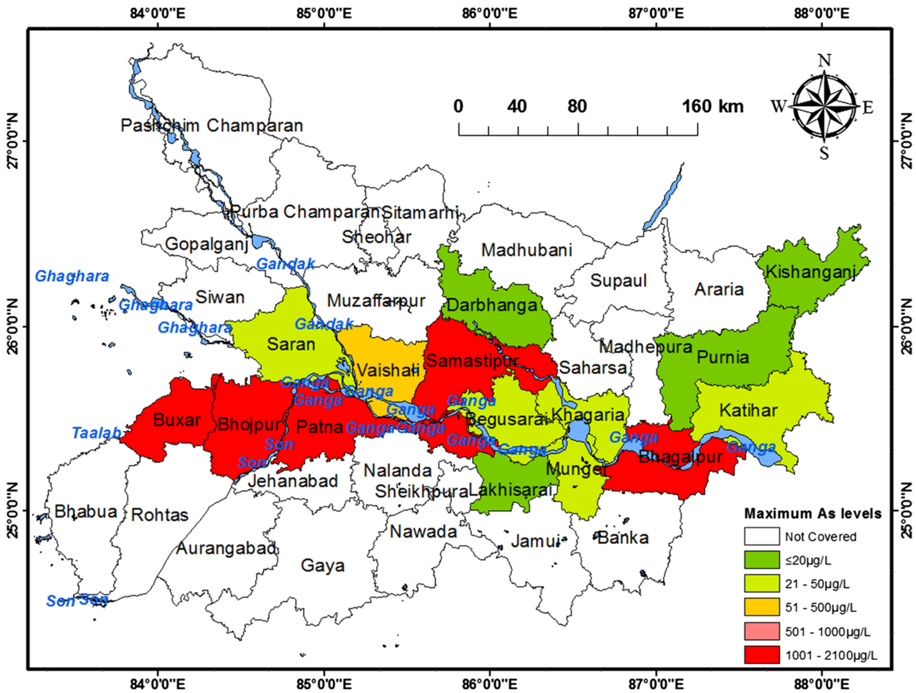

Fig. 4 Arsenic contaminated districts of Bihar. The map is based on more than 30,000 drinking water sources tested for *As* concentrations, pooled from several published sources. The mean value of *As* exceed the BIS standards set for drinking water; however, the map represents the highest concentration detected in the areas (SOES 2006; Ghosh et al. 2007; Saha 2009; Singh 2011)

3.3 Mapping sensitivity

3.3.1 Mapping socioeconomic–demographic vulnerability

A total of five districts including Vaishali, Samastipur, Darbhanga, Purnia, and Katihar were found to be socioeconomically and demographically highly vulnerable (Fig. 5). Among these districts, only Samastipur falls in the 500–1,000 µg/L *As* contamination range (Fig. 4). Among the highly *As*-affected districts (>1,000 µg/L) and highly *As* vulnerable populations, only Patna district was found to be socioeconomically and demographically moderately vulnerable (Figs. 4, 7). The socioeconomic–demographic vulnerability is a function of the population below the poverty line, population growth, population density, SCs, and STs population (representing the lowest rungs of the caste hierarchy). The socioeconomic–demographic vulnerability map explicates that in spite of having a higher concentration of *As* and a highly vulnerable population size, the socioeconomic and demographic conditions of the exposed population reduced the vulnerability in the high *As*-contaminated areas and magnified the vulnerability in the areas with lower levels of *As* contamination. With more than 1,000 µg/L of *As* levels in the groundwater, Buxar, Bhojpur, and Bhagalpur districts were found to be socioeconomically and demographically at risk, which is the second level at the vulnerability index and only rank behind to reach the resilient stage, whereas the districts with *As*

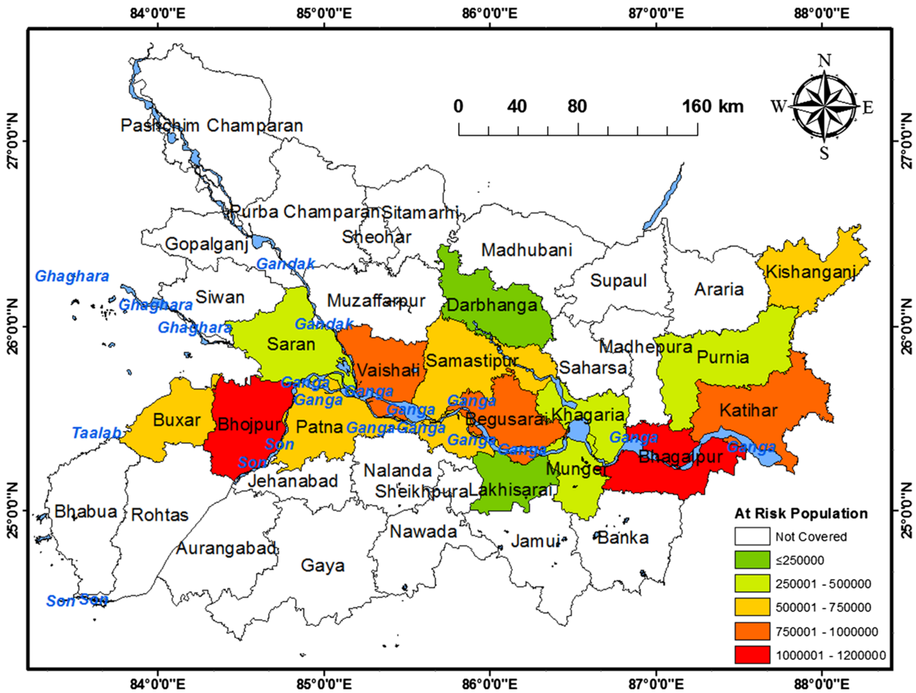

Fig. 5 Arsenic vulnerable population of Bihar

levels between 51 and 1,000 µg/L of *As* including Vaishali and Samastipur were found to be socioeconomically and demographically highly vulnerable. Moreover, Darbhanga, Purnia, and Katihar, which are comparatively less *As*-contaminated (<*As* 20 µg/L), were the other three highly vulnerable because of the poor socioeconomic and demographic conditions. Only two districts Lakhisarai (because of the lowest number of the most vulnerable population (STs) and the lowest population density) and Munger (because of the lowest population density in the areas) were found to be resilient districts in the state.

3.3.2 Mapping health vulnerability

The population of Bihar is affected by several diseases such as diarrhea, tuberculosis, filarial, polio, and kala-azar that are endemic in the state. This study demonstrates that Katihar and Patna districts were highly vulnerable due to very poor health conditions, followed by moderately vulnerable district Vaishali, less vulnerable districts Saran, Samastipur, Khagaria, and Purnia, and the at-risk districts Lakhisarai, Bhagalpur, Darbhanga, and Kishanganj (Fig. 8). In Katihar, the infant mortality rate (59 %) and the HIV prevalence (2.5 %) were very high, and in Patna, the tuberculosis incidence (8.5 %) was the highest among other districts (BRLPS 2007). In the moderately vulnerable district Vaishali, the kala-azar prevalence was the highest (11.4) followed by a high tuberculosis incidence of 4.3 (BRLPS 2007). People with poor health will be more susceptible to Arsenicosis; they lack the required physiological coping mechanism against any foreign

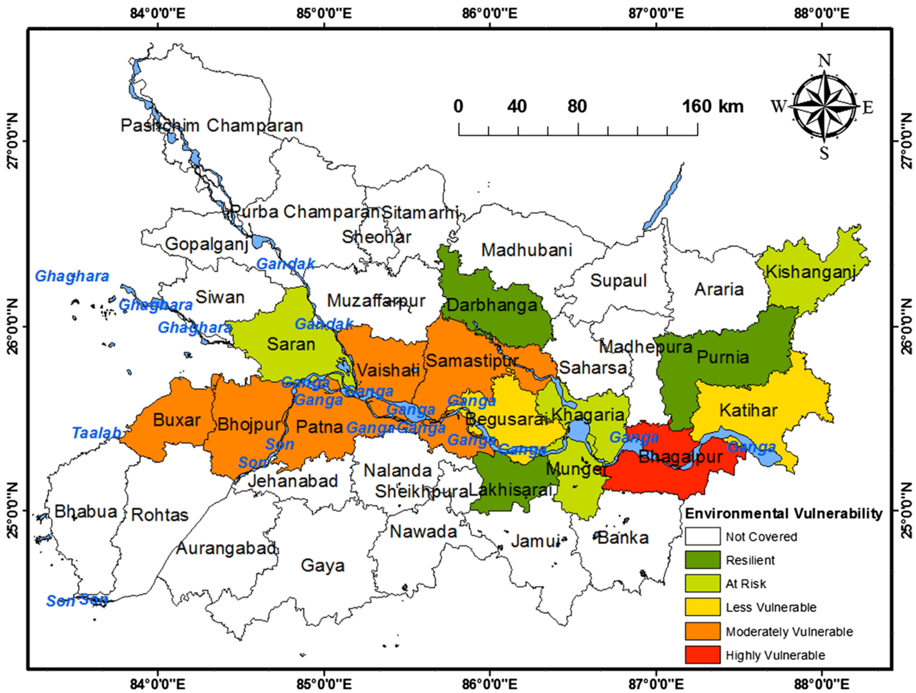

Fig. 6 Environmental vulnerability map of Bihar

agents in the body, therefore making them more vulnerable and sensitive to any additional health problems.

3.3.3 Mapping geological vulnerability

Geologically, Darbhanga, Katihar, Khagaria, Kishanganj, and Purnia were found to be highly vulnerable as the lithology of the areas is shaped by only younger alluvium, which has been reported as the highly *As*-contaminated areas in the state. However, all these districts are on the northern side of the River Ganges and have not been investigated for groundwater *As* contamination (Figs. 4, 9). The moderately vulnerable districts were Buxar, Bhojpur, Saran, Vaishali, Samastipur, and Begusarai. All these districts except Begusarai have been found to be highly *As*-contaminated areas. The lithology of these districts is mainly shaped by the younger alluvial and calcareous alluvial soil.

3.4 Mapping adaptive capacity

Kishanganj, Purnia, and Katihar were found to be the highly vulnerable areas because of they have the lowest adaptive capacities (Fig. 10). The total literacy rates and the female literacy rates in these districts were far below the average literacy rates in the state (BRLPS 2007). Katihar and Purnia both had a total literacy rate of only 35.1 %, whereas Kishanganj

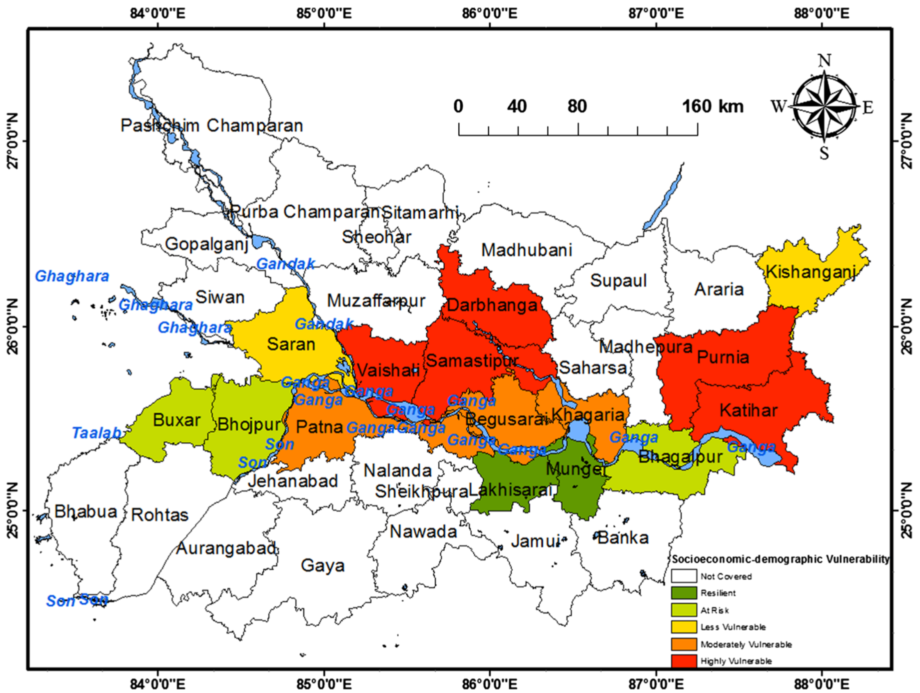

Fig. 7 Socioeconomic–demographic vulnerability map of Bihar

had the lowest total literacy rate of only 31 % among all other districts (BRLPS 2007). Two highly *As*-affected districts Bhojpur and Patna, along with one of the lowest *As*-affected districts, Munger, were the resilient areas with higher literacy rates (Fig. 10). Other highly *As*-affected areas Buxar and Bhagalpur were at risk followed by Samastipur (Fig. 10).

3.5 Mapping composite vulnerability

A composite vulnerability map (CVM) is the map based on the average mean value of all the vulnerability indexes covered in this study. It is important to mention here that the VI values for *exposure* and *sensitivity* trended in a positive direction (the greater the VI, greater the vulnerability). However, for *adaptive capacity,* the VI values trended in a negative direction (the greater the VI, less adaptive capacity). The CVM elucidates that Katihar was the only district found to be a highly vulnerable area, followed by the moderately vulnerable areas of Vaishali, Samastipur, Khagaria, and Purnia; less vulnerable areas were Buxar, Patna, Begusarai, Bhagalpur, Saran, Darbhanga, and Kishanganj districts, respectively (Fig. 11). The Bhojpur and Lakhisarai districts were found to be the districts at risk. Only one district, Munger, was found to be resilient with comparatively higher adaptive capacities (Fig. 11). Surprisingly, between the two at-risk districts, Bhojpur was one of the highly *As*-contaminated districts, with *As* levels in the groundwater of more than 1,000 μg/L (Fig. 4).

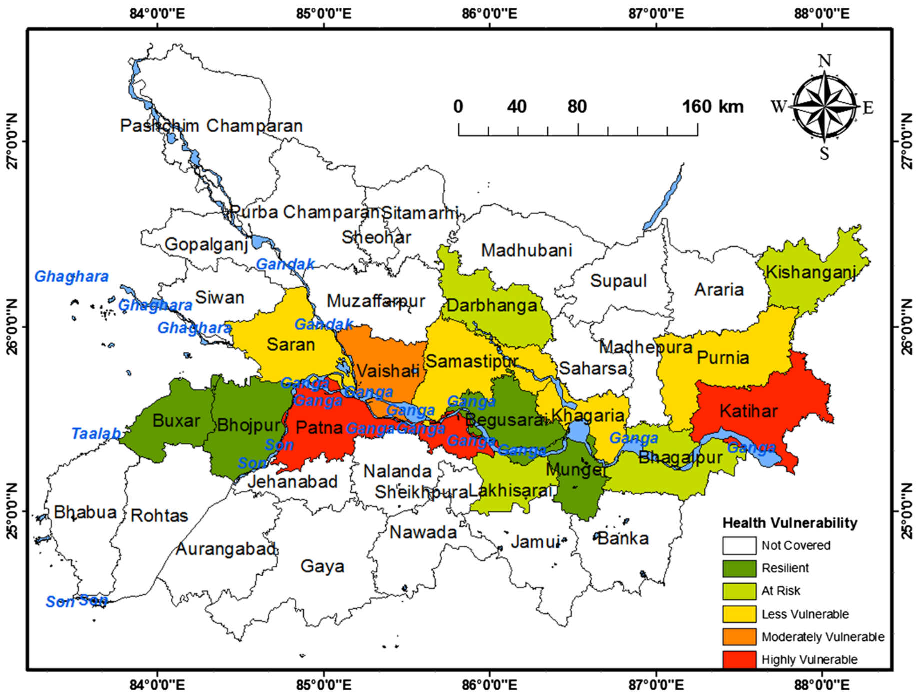

Fig. 8 Health vulnerability map of Bihar

Additionally, the study suggests that besides higher concentrations of a carcinogenic material (arsenic in this case), other biophysical, socioeconomic, demographic, educational, health, and environmental factors have a significant effect on the total vulnerability in the area. Therefore, a CVM could be a very important decision-making tool to evaluate the actual vulnerable areas as a function of composite vulnerability indicators. Among the highly *As*-affected districts, which include Buxar, Bhojpur, Patna, and Bhagalpur (As > 1,000 μg/L), Bhojpur dropped two levels on the vulnerability index scale and improved to be classified as an "at-risk" district (Fig. 11). The other three districts dropped one level to being less vulnerable areas (Fig. 11). These findings suggest that vulnerability of the area or the communities in the state do not depend entirely on the environmental stressors like groundwater contaminations or other environmental hazards. Other factors, including the socioeconomic and demographic status of the communities and geological properties of the areas, play a vital role in shaping the total vulnerability of the population and the region. These finding are in line with previous studies, which argue that there is a need for multiple indicators to adequately assess the vulnerability of areas impacted by natural hazards (Cutter et al. 2009).

3.6 Principal component analysis

According to the correlation matrix, a significant positive correlation between rural population, flood incidence, and geological formation was found (Appendix 1). This positive correlation suggests that flood incidences are more prevalent in rural areas, and

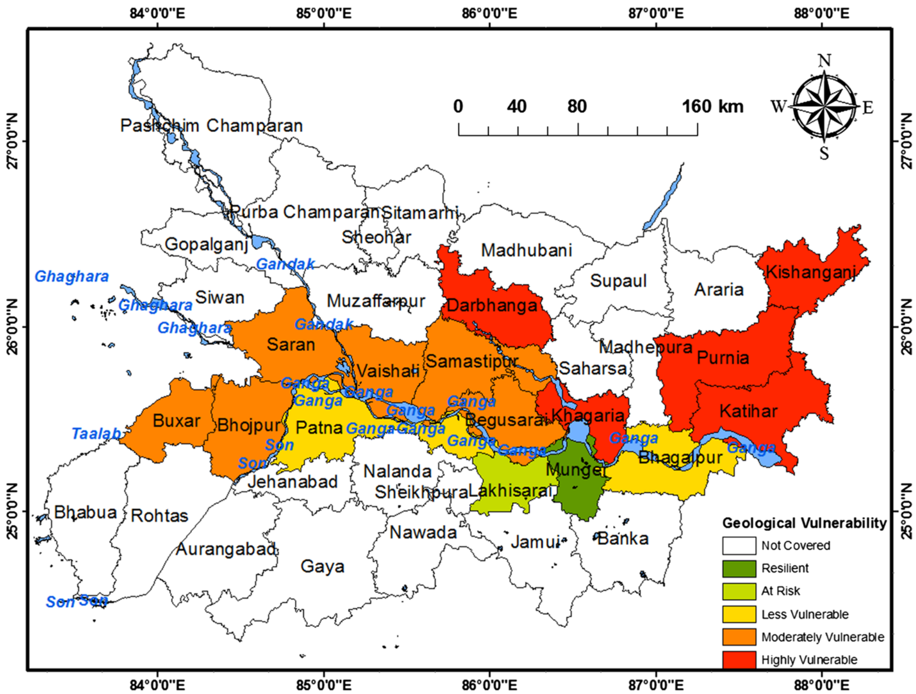

Fig. 9 Geological vulnerability map of Bihar

the geological formation is of quaternary age. These factors will contribute to the vulnerability in the rural areas in the state. Furthermore, a very high positive correlation between BPL, kala-azar prevalence, TB incidences, flood incidences, lithology of the areas, and physiography of the areas was also derived (Appendix 1). A high positive correlation was found between the SC population and population density. Total literacy and female literacy were found to be significantly negatively correlated with the ST population. Population growth only had a strong negative correlation with total literacy but was found to be strongly positively correlated with the lithology and the physiography of the areas. This further explains that population growth is greater in the areas with younger alluvial soil and in the alluvial plain in the state. Population density showed a strong positive correlation with kala-azar prevalence and TB incidence (Appendix 1).

Communalities of one-third of the variables were close to 1 and were reasonably high for the rest of the variables, with only one variable drought incidence (.566) close to the lower end of the acceptable value (Appendix 2). The extracted principal components have been represented in Table 3.

The eigenvalues in the extracted five components that were found to be greater than one ranged between 1.2 and 6.8 (Table 3). The first principal components explain about 33 % of the variance; the second components accounted for 21 % of the variance; the third with 14.3 % of the variance; the fourth components for 7.5 %; and the fifth components for 5.9 % of the variance (Table 3). Together, the first five components accounted for a cumulative 81.6 % of the variance in the vulnerability data set.

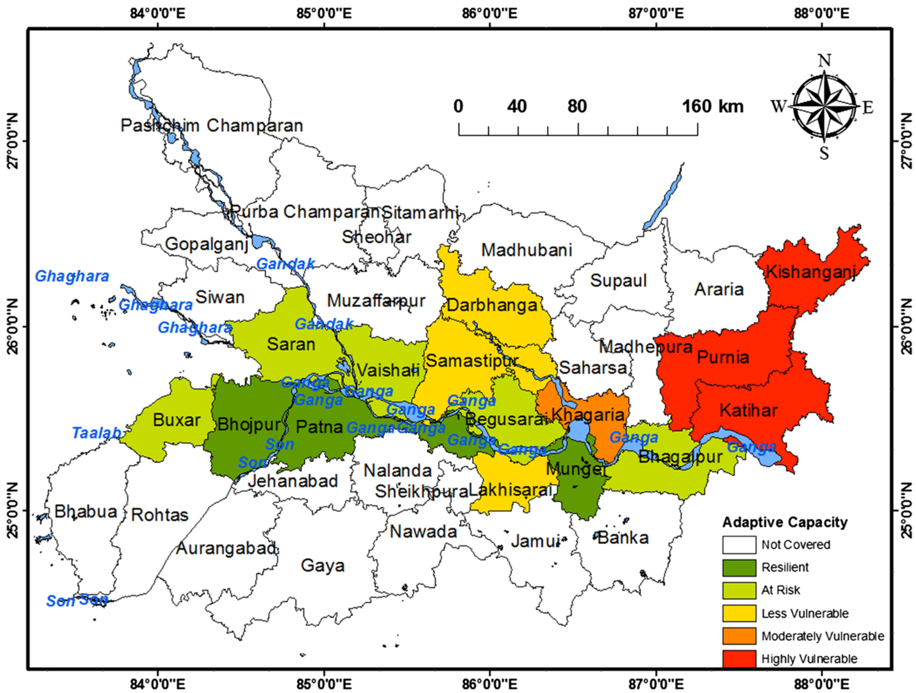

Fig. 10 Adaptive capacity map of Bihar

The first PC contrasts the total literacy, female literacy, *F*-affected districts, and drought incidence with other variables in the component. As discussed earlier, literacy rates (both total literacy rate and female literacy rate) reduce total vulnerability, as they constitute a very important component of the adaptive capacity of the communities. The extreme negative loadings of total literacy rate (−.942) and female literacy rate (−.930) reflect that the composite vulnerability is highly negatively affected by adaptive capacity (Table 4). The sensitivity indicators, lithology (.760) and infant mortality rate (.740) with comparatively higher loadings, indicate that the composite vulnerability is affected by the *sensitivity* of the areas. Other variables with loadings close to zero indicate an average contribution to composite vulnerability (Saha and Shukla 2013). The second PC was primarily marked by high positive loadings of eight sensitivity indicators with only one variable geological formation with negative loading (Table 4). The third component was marked by only the sensitivity indicators. The fourth component and the fifth component were marked, respectively, with only three elements and two elements with loadings more than .40.

The bend that appears on the scree plot also suggests that the variance will essentially be explained by the five PCs (Appendix 3). A loading of more than .40 of each variable in each component was interpreted and was considered in naming the components (Warner 2012). The first component had high loadings of a total of 16 variables; both the adaptive capacity indicators, total literacy rate and female literacy rate, had the highest loadings (Table 4). Furthermore, five exposure indicators out of a total of six and nine sensitivity indicators out of a total of thirteen indicators were the other

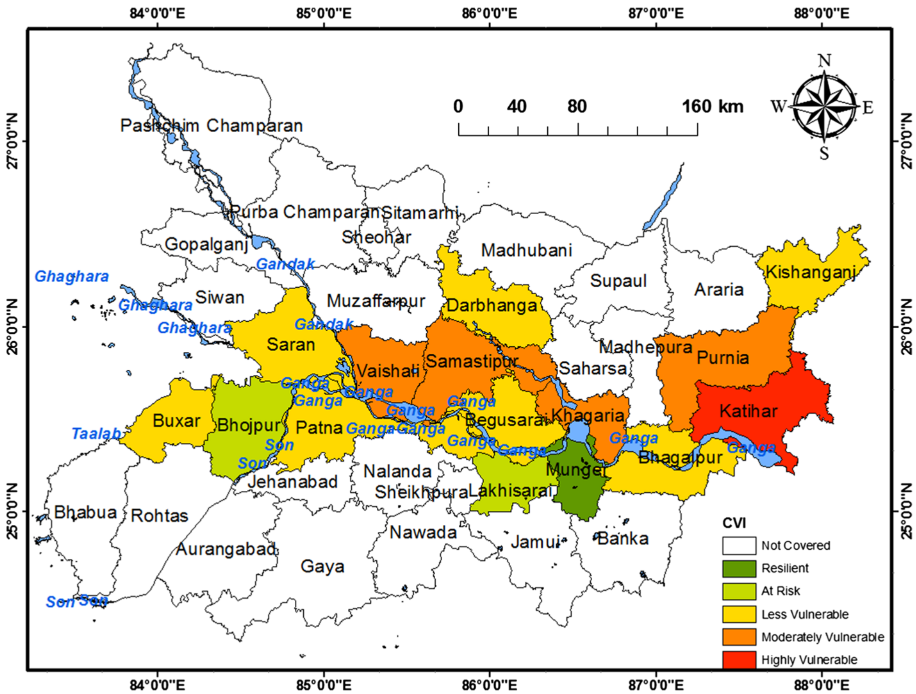

Fig. 11 Composite vulnerability map showing total vulnerability in Bihar

Table 3 Eigenvalues of the principal components

Component	Initial eigenvalues			Extraction sums of squared loadings		
	Total	% of variance	Cumulative (%)	Total	% of variance	Cumulative (%)
Total variance explained						
1	6.891	32.812	32.812	6.891	32.812	32.812
2	4.423	21.063	53.875	4.423	21.063	53.875
3	3.003	14.298	68.173	3.003	14.298	68.173
4	1.584	7.542	75.716	1.584	7.542	75.716
5	1.235	5.882	81.598	1.235	5.882	81.598
6	.922	4.392	85.990			
7	.877	4.174	90.164			
8	.766	3.650	93.814			

Extraction method: principal component analysis

elements in the first component, with more than .40 loadings. Based on the *RNPC*, the first component could be labelled "Adaptive Capacity"; the second and the third component as "Sensitivity"; and the fourth and the fifth component as "Exposure" (Table 4). The fifth component had only two variables with loadings more than .40, each from exposure and sensitivity. Considering the comparatively higher loading of the

Table 4 Loading matrix of the principal components

	Component				
	Adaptive capacity	Sensitivity	Sensitivity	Exposure	Exposure
Component matrix[a]					
Total literacy	**−.942**	−.036	−.147	.113	.073
Female literacy	**−.930**	.105	−.150	.043	−.084
Lithology	**.760**	**.451**	.123	.265	.053
Infant mortality rate	**.740**	−.277	.105	−.018	−.185
Flood incidence	**.717**	.373	−.124	−.060	−.082
Fluoride-affected districts	**−.660**	−.139	.390	.030	−.324
Rural population	**.651**	.038	**−.588**	.353	.079
Population growth	**.561**	**.417**	.355	.221	−.188
Arsenic-affected districts	**−.557**	.311	−.102	**.511**	−.047
Nitrate-affected districts	**−.550**	.155	.248	.398	−.344
Drought incidence	**−.477**	−.362	.364	.270	.050
Population density	−.311	**.842**	−.240	−.061	.053
Below the poverty line population	**.438**	**.797**	.228	−.194	.086
Tuberculosis incidence	−.372	**.796**	.314	−.130	.212
Kala-azar prevalence	.075	**.684**	−.388	−.289	−.187
Physiography	.357	**.636**	.032	**.629**	−.253
HIV prevalence	−.039	.223	**.761**	−.011	**.514**
Scheduled caste population	−.392	**.462**	**−.658**	−.082	.294
Scheduled tribe population	**.620**	−.143	**.628**	−.153	−.077
Geological formation	**.502**	−.492	**−.555**	−.016	−.162
Iron-affected districts	.363	−.411	−.122	**.510**	**.610**

Bold values indicate the significant loading values greater than 0.40

Extraction method: principal component analysis

[a] 5 Components extracted

iron-affected district (.610) over the HIV prevalence (.514), we named the fifth component "Exposure."

4 Conclusion

There exists a unique combination of biophysical and socioeconomic conditions in Bihar, making it highly vulnerable to the effects of groundwater *As* contamination. The CVM shows that Katihar is the only "highly vulnerable" district, followed by the "moderately vulnerable" areas of Vaishali, Samastipur, Khagaria, and Purnia, and the "less vulnerable" areas of Buxar, Patna, Begusarai, Bhagalpur, Saran, Darbhanga, and Kishanganj, respectively. Bhojpur and Lakhisarai districts were found to be "at risk." Only Munger was found to be a "resilient" district with a comparatively higher coping capacity. Vaishali, Samastipur, and Katihar districts should be given priority in *As*-mitigation plans; low-cost *As*-mitigation technology(s) would be the best fit for Vaishali and Purnia followed by Darbhanga, Katihar, Samastipur, and Begusarai, respectively. The Bhojpur district would be an ideal *As*-affected district to begin with an *As*-mitigation plan.

The CVM of Bihar has three major potential uses: first, to identify the “highly vulnerable” areas where *As* mitigation is the most urgent requirement; second, to identify types of feasible and sustainable *As*-mitigation options for a specific vulnerable area; and third, to identify the area(s) where the likelihood of success of an *As*-mitigation plan is greatest (Fig. 11). Our study demonstrates that among the 15 *As*-affected districts, Katihar can be considered “highly vulnerable”; therefore, this district should be given priority in an *As*-mitigation plan where *As* mitigation is an urgent necessity. Although Katihar has very low levels of *As* concentration, socioeconomically and demographically, health wise, and geologically, it is one of the “highly vulnerable” areas in the state with the least adaptive capacity. *As*-mitigation policy should accord the next highest priority to Buxar, Patna, Begusarai, Bhagalpur, and Saran followed by other *As*-contaminated districts including Vaishali, Samastipur, and Khagaria. Although Bhojpur was among the highly *As*-affected districts, because of its high level of adaptive capacity, it was found to be “at risk.” Therefore, the likelihood of success of an *As*-mitigation program in this district is very high. Vaishali, Samastipur, Khagaria, and Purnia are the “moderately vulnerable” areas that are socioeconomically and demographically heterogeneous in nature and fall under the socioeconomically and demographically highly vulnerable areas in the state. Therefore, the expensive *As*-mitigation options would not work in any of these districts. Considering the adaptive capacity of these three “highly vulnerable” districts, Vaishali has a better adaptive capacity than the other districts. Therefore, among the “moderately vulnerable” districts, Vaishali should be given priority, followed by Samastipur with low-cost *As*-mitigation policies.

The PCA suggests that the five principal components essentially explain the variance in composite vulnerability. The total literacy rate, the female literacy rate, rural population, population growth, population below the poverty line, scheduled caste population, infant mortality rate, flood incidence, drought incidence, *As*, *F*, *N*, lithology, and the geological formation were found to be the most important variables to explain the variance of composite vulnerability. The first component was the adaptive capacity, which further suggests that the adaptive capacity of the communities makes relatively greater contributions to reduce the total vulnerability. Moreover, other indicators of adaptive capacity could be identified and studied to derive total vulnerability in areas under multiple environmental and social stressors. For instance, additional information about people’s risk perception of the *As* problem, the presence and functionality of institutions, interpersonal trust, and trust in institutions working in those areas would be very helpful in understanding the adaptive capacity of the exposed communities. In our ongoing study, we gathered household-level information about these indicators along with other socioeconomic and demographic variables in three *As*-affected villages in Bihar, India, which would be incorporated in the proposed vulnerability framework, and a CV could be derived at the household level. This will make the CV decision-making tool more precise. The empirical data from these three *As*-affected villages would help calibrate the CVM and will testify to the predictive capacity of the CVM.

Acknowledgments The authors would like to thank Dr. Amy V. Ferdinand, Director, Environmental Health and Safety and Ms. Rocio Duchesne, Department of Earth and Environmental Studies, Montclair State University, for their support in GIS mapping. The authors also extend their gratitude to the three anonymous reviewers for their constructive feedback, which helped to significantly improve the quality of this manuscript.

Appendix 1

See Table 5.

Table 5 Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11
RP(1)	1										
BPL(2)	.110	1									
SCP(3)	.086	.098	1								
STP(4)	.050	.369	**−.765****	1							
PG(5)	.207	.502	−.298	.369	1						
PD(6)	.016	.442	**.598***	−.478	.113	1					
TL(7)	−.501	−.506	.445	**−.687****	**−.572***	.288	1				
FL(8)	−.487	−.390	.493	**−.687****	−.440	.428	**.888****	1			
IMR(9)	.298	.191	−.447	**.517***	.272	**−.616***	**−.732****	**−.711****	1		
KZP(10)	.192	**.591***	.507	−.193	.084	**.608***	−.132	.043	−.021	1	
TBI(11)	−.378	**.595***	.349	−.067	.072	**.743****	.291	.341	**−.541***	.356	1
HIVP(12)	−.402	.378	−.202	.401	.202	.042	−.084	−.061	−.020	−.190	**.551***
Flood(13)	**.538***	**.635***	−.027	.390	.461	.116	**−.724****	**−.578***	.344	.261	.026
Drought(14)	−.348	−.452	−.314	.023	−.274	−.164	.344	.362	−.381	−.333	−.029
As(15)	−.122	.009	.428	−.415	−.256	.304	**.564***	**.577***	−.354	.188	.375
F(16)	**−.696****	−.302	−.128	−.136	−.151	−.050	**.573***	**.612***	−.299	−.324	.173
N(17)	−.398	−.176	.020	−.250	−.151	.164	.458	.473	−.299	−.061	.317
Fe(18)	.485	−.200	−.096	.060	−.017	−.468	−.203	−.395	.314	−.458	−.460
GF(19)	**.705****	−.312	−.139	.161	−.184	−.405	−.406	−.395	.434	−.031	**−.716****
Lithology(20)	.489	**.612***	−.188	.365	**.789****	.118	**−.652****	**−.678****	.437	.213	.060
Physiography(21)	.453	**.523***	−.013	.089	**.652****	.381	−.298	−.217	.106	.296	.263

Table 5 continued

	12	13	14	15	16	17	18	19	20	21
RP(1)										
BPL(2)										
SCP(3)										
STP(4)										
PG(5)										
PD(6)										
TL(7)										
FL(8)										
IMR(9)										
KZP(10)										
TBI(11)										
HIVP(12)	1									
Flood(13)	−.090	1								
Drought(14)	.267	−.492	1							
As(15)	.032	−.195	.256	1						
F(16)	.109	−.431	.364	.463	1					
N(17)	.109	−.431	.364	.463	.318	1				
Fe(18)	.081	.055	.040	−.028	−.342	−.342	1			
GF(19)	**−.548***	.327	−.161	−.312	−.443	−.443	.286	1		
Lithology(20)	.160	**.542***	−.483	−.281	**−.577***	−.224	.230	.021	1	
Physiography(21)	.011	.480	−.237	.322	−.207	.237	.026	−.105	**.720****	1

The bold values are statistically significant values

* Correlation is significant at the .05 level (two-tailed)

** Correlation is significant at the .01 level (two-tailed)

Appendix 2

See Table 6.

Table 6 Communalities table

	Initial	Extraction
Communalities		
Rural population	1.000	.902
Below the poverty line population	1.000	.923
Scheduled caste population	1.000	.894
Scheduled tribe population	1.000	.829
Population growth	1.000	.699
Population density	1.000	.870
Total literacy	1.000	.928
Female literacy	1.000	.908
Infant mortality rate	1.000	.670
Kala-azar prevalence	1.000	.743
Tuberculosis incidence	1.000	.933
HIV prevalence	1.000	.894
Flood incidence	1.000	.678
Drought incidence	1.000	.566
Arsenic-affected districts	1.000	.681
Fluoride-affected districts	1.000	.713
Nitrate-affected districts	1.000	.664
Iron-affected districts	1.000	.949
Geological formation	1.000	.830
Lithology	1.000	.870
Physiography	1.000	.993

Extraction method: principal component analysis

Appendix 3

See Fig. 12.

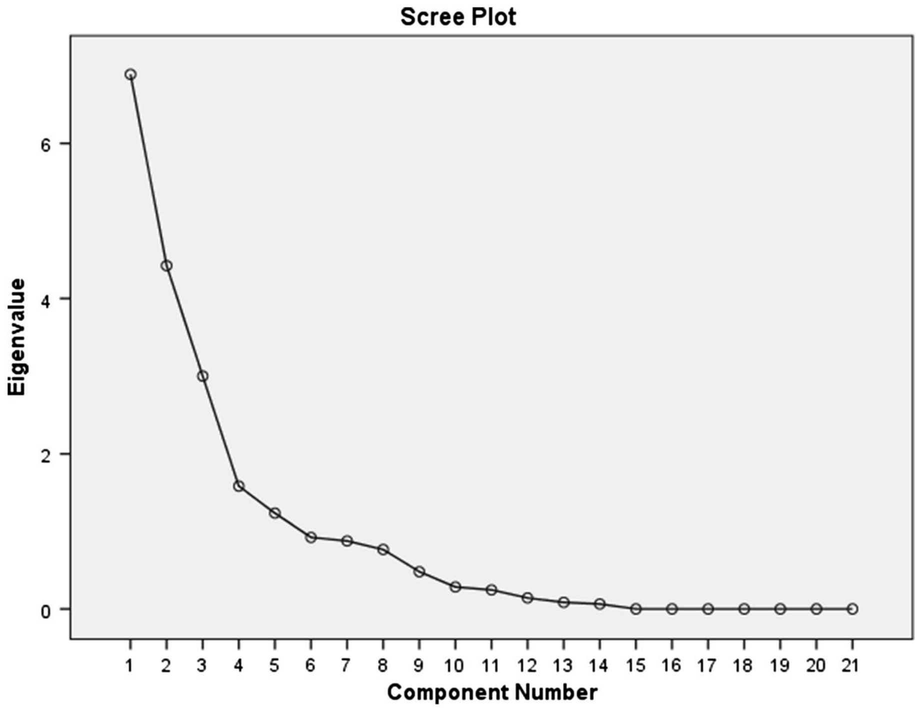

Fig. 12 Scree plot

References

Adger WN, Brooks N, Bentham G, Agnew M, Eriksen S (2004) New indicators of vulnerability and adaptive capacity. Tyndall Centre for Climate Change Research Norwich

BAMETI (2014) Agriculture profile of the state-Bihar. Bihar Agricultural Management and Extension-Training Institute (BAMETI)

Banerjee M, Banerjee N, Bhattacharjee P, Mondal D, Lythgoe PR, Martínez M, Pan J, Polya DA, Giri AK (2013) High arsenic in rice is associated with elevated genotoxic effects in humans. Scientific reports 3

Bates KA, Swan RS (2007) Through the eye of Katrina: social justice in the United States. Carolina Academic Press, Durham

Bihardays T (2011) How girls from arsenic-hit villages can't get married: along the UP-Bihar border!. Bihardays, Bihar

Birkmann J, Cardona OD, Carreño ML, Barbat AH, Pelling M, Schneiderbauer S, Kienberger S, Keiler M, Alexander D, Zeil P, Welle T (2013) Framing vulnerability, risk and societal responses: the MOVE framework. Nat Hazards 67(2):193–211

BIS (2012) Indian standard DRINKING WATER—SPECIFICATION (second revision): is 10500: 2012, Bureau of Indian Standards, Manak Bhavan, 9 Bahadur Shah Zafar Marg, New Delhi 110002, India

Brinkel J, Khan MH, Kraemer A (2009) A systematic review of arsenic exposure and its social and mental health effects with special reference to Bangladesh. Int J Environ Res Public Health 6(5):1609–1619

BRLPS (2007) Poverty and social assessment: a district wise study of Bihar. Bihar rural livelihood project Bihar rural livelihoods promotion society (BRLPS), State Rural Livelihoods Mission (SRLM), Bihar, India

BSPCB M (2007) State of environment report, Bihar, Bihar State Pollution Control Board, Patna and Ministry of Environment and Forest, Government of Bihar, India

Census (2013) Annual Health Survey 2011–2012 fact sheet, Vital Statistics Division, office of the Registrar General and Census Commissioner, New Delhi, India

Center H (2002) Human links to coastal disasters. The H. John Heinz III Center for Science, Economics and the Environment, Washington, DC

Chakraborti D, Mukherjee SC, Pati S, Sengupta MK, Rahman MM, Chowdhury UK, Lodh D, Chanda CR, Chakraborti AK, Basu GK (2003) Arsenic groundwater contamination in Middle Ganga Plain, Bihar, India: a future danger? Environ Health Perspect 111(9):1194

Chowdhury UK, Biswas BK, Chowdhury TR, Samanta G, Mandal BK, Basu GC, Chanda CR, Lodh D, Saha KC, Mukherjee SK (2000) Groundwater arsenic contamination in Bangladesh and West Bengal, India. Environ Health Perspect 108(5):393

Cord L, Verhoeven M, Blomquist C, Rijkers B (2009) The global economic crisis: assessing vulnerability with a poverty lens. World Bank research note, Washington, DC

Cox J, Rosenzweig C, Solecki W, Goldberg R, Kinney P (2006) Social vulnerability to climate change: a neighborhood analysis of the Northeast US megaregion. Draft white paper for Union of Concerned Scientists, Northeast Climate Change Impact Study. http://www.northeastclimateimpacts.org/pdf/tech/cox_et_al.pdf

Cutter SL, Finch C (2008) Temporal and spatial changes in social vulnerability to natural hazards. Proc Natl Acad Sci 105(7):2301–2306

Cutter SL, Barnes L, Berry M, Burton C, Evans E, Tate E, Webb J (2008) A place-based model for understanding community resilience to natural disasters. Glob Environ Change 18(4):598–606

Cutter SL, Emrich CT, Webb JJ, Morath D (2009) Social vulnerability to climate variability hazards: a review of the literature. Final report to Oxfam America, pp 1–44

Das RJ (1999) Geographical unevenness of India's green revolution. J Contemp Asia 29(2):167–186

Datta D, Kaul M (1976) Arsenic content of drinking water in villages in Northern India. A concept of arsenicosis

ESRI (2012) ArcGIS for Desktop 10.1, Environmental Systems Research Institute

Ghosh A, Singh S, Bose N, Ramanathan A, Bhattacharya P, Keshari A (2005). Arsenic hot spots detected in the State of Bihar (India) a serious health hazard for estimated human population of 5.5 Lakhs. International Conference on Environmental Management, Hyderabad, India

Ghosh A, Singh S, Bose N, Chowdhary S (2007) Arsenic contaminated aquifers: a study of the Ganga levee zone in Bihar, India. Symposium on Arsenic: The Geography of a Global Problem, Royal Geographical Society, London. http://www.geog.cam.ac.uk/research/projects/arsenic

Ghosh AK, Singh SK, Singh SK, Singh A, Roy N, Upadhyaya A, Bose N, Chaudhary S, Mishra R (2008) Study of arsenic contamination in ground water of Bihar, (India) along the river ganges. Water Energy Abstr 18(1):19–20

GSI (2012) Geology and mineral resources of eastern region. Geological Survey of India (GSI), Kolkata, India

Guha Mazumder D, Dasgupta U (2011) Chronic arsenic toxicity: studies in West Bengal, India. Kaohsiung J Med Sci 27(9):360–370

Guillard-Gonçalves C, Cutter SL, Emrich CT, Zêzere JL (2014) Application of social vulnerability index (SoVI) and delineation of natural risk zones in Greater Lisbon, Portugal. J Risk Res (ahead-of-print):1–24. doi:10.1080/13669877.2014.910689

Hossain MA, Mukharjee A, Sengupta MK, Ahamed S, Das B, Nayak B, Pal A, Rahman MM, Chakraborti D (2006) Million dollar arsenic removal plants in West Bengal, India: useful or not? Water Qual Res J Can 41(2):216–225

IPCC (2007) Assessing key vulnerabilities and the risk from climate change. In: Parry ML, Canziani OF, Palutikof JP, van der Linden PJ, Hanson CE (eds) Climate change 2007: impacts, adaptation and vulnerability, contribution of working group II to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge, pp 7–72

Kienberger S, Lang S, Zeil P (2009) Spatial vulnerability units–expert-based spatial modelling of socio-economic vulnerability in the Salzach catchment, Austria. Nat Hazards Earth Syst Sci 9(3)

Lado LR, Polya D, Winkel L, Berg M, Hegan A (2008) Modelling arsenic hazard in Cambodia: a geo-statistical approach using ancillary data. Appl Geochem 23(11):3010–3018

Mandal BK, Suzuki KT (2002) Arsenic round the world: a review. Talanta 58(1):201–235

Mazumder DNG, Ghosh A, Majumdar KK, Ghosh N, Saha C, Mazumder RNG (2010) Arsenic contamination of ground water and its health impact on population of district of Nadia, West Bengal, India. Indian J Commun Med 35(2):331

Mukherjee A, Sengupta MK, Hossain MA, Ahamed S, Das B, Nayak B, Lodh D, Rahman MM, Chakraborti D (2006) Arsenic contamination in groundwater: a global perspective with emphasis on the Asian scenario. J Health Popul Nutr 24(2):142–163

Mukherjee A, Scanlon BR, Fryar AE, Saha D, Ghosh A, Chowdhuri S, Mishra R (2012) Solute chemistry and arsenic fate in aquifers between the Himalayan foothills and Indian craton (including central Gangetic plain): Influence of geology and geomorphology. Geochim Cosmochim Acta 90:283–302

Nickson R, Sengupta C, Mitra P, Dave S, Banerjee A, Bhattacharya A, Basu S, Kakoti N, Moorthy N, Wasuja M (2007) Current knowledge on the distribution of arsenic in groundwater in five states of India. J Environ Sci Health Part A 42(12):1707–1718

Nordstrom DK (2002) Worldwide occurrences of arsenic in ground water. Science (Washington) 296(5576):2143–2145

Papathoma-Köhle M, Kappes M, Keiler M, Glade T (2011) Physical vulnerability assessment for alpine hazards: state of the art and future needs. Nat Hazards 58(2):645–680

Parry ML (2007) Climate change 2007: impacts, adaptation and vulnerability: contribution of Working Group II to the fourth assessment report of the intergovernmental panel on climate change. Cambridge University Press, Cambridge

Phillips B, Fordham M (2009) Introduction: chapter 1. Social vulnerability to disasters. CRC Press, Boca Raton

Rahman MM, Mondal D, Das B, Sengupta MK, Ahamed S, Hossain MA, Samal AC, Saha KC, Mukherjee SC, Dutta RN (2013) Status of groundwater arsenic contamination in all 17 blocks of Nadia district in the state of West Bengal, India: A 23-year study report. J Hydrol. doi:10.1016/j.jhydrol.2013.10.037

Ravenscroft P, Brammer H, Richards K (2011) Arsenic pollution: a global synthesis. Wiley, New York

Saha D (2009) Arsenic groundwater contamination in parts of middle Ganga plain, Bihar. Curr Sci 97(6):753–755

Saha D, Shukla R (2013) Genesis of Arsenic-Rich Groundwater and the Search for Alternative Safe Aquifers in the Gangetic Plain, India. Water Environ Res 85(12):2254–2264

Saha D, Dhar Y, Sikdar P (2008) Geochemical evolution of groundwater in the Pleistocene aquifers of south Ganga plain, Bihar. J Geol Soc India 71(4):473

Saha D, Dwivedi S, Sahu S (2009) Arsenic in ground water in parts of middle ganga plain in Bihar-an appraisal. Editor Board 24(2&3):82–94

Saha D, Sarangam SS, Dwivedi SN, Bhartariya KG (2010) Evaluation of hydrogeochemical processes in arsenic-contaminated alluvial aquifers in parts of Mid-Ganga Basin, Bihar, Eastern India. Environ Earth Sci 61(4):799–811

Saha D, Sahu S, Chandra P (2011) Arsenic-safe alternate aquifers and their hydraulic characteristics in contaminated areas of Middle Ganga Plain, Eastern India. Environ Monit Assess 175(1–4):331–348

Schmidtlein MC, Deutsch RC, Piegorsch WW, Cutter SL (2008) A sensitivity analysis of the social vulnerability index. Risk Anal 28(4):1099–1114

Singh S (2011) Arsenic contamination in water, soil, and food materials in Bihar. LAP LAMBERT Academic Publishing, Germany

Singh SK, Ghosh AK (2012) Health risk assessment due to groundwater arsenic contamination: children are at high risk. Human Ecol Risk Assess Int J 18(4):751–766

Singh KM, Jha A (2012) Innovative approaches in technology dissemination: experiences of ATMA model in Bihar. Available at SSRN 2168646

Singh S, Ghosh A, Kumar A, Kislay K, Kumar C, Tiwari R, Parwez R, Kumar N, Imam M (2014) Groundwater arsenic contamination and associated health risks in Bihar, India. Int J Environ Res 8(1):49–60

SOES (2006) Groundwater arsenic contamination in West Bengal, India (20 years study). Retrieved June 6, 2014, from http://www.soesju.org/arsenic/wb.htm

SPSS I (2012) IBM SPSS statistics version 21. International Business Machines Corp, Boston, Mass

Tierney KJ (2001) Facing hazards and disasters: understanding human dimensions. National Academy Press, Washington, DC

Tierney KJ, Lindell MK, Perry RW (2001) Facing the unexpected: disaster preparedness and response in the United States, Joseph Henry Press, Washington, DC

UNEP (2003) Assessing human vulnerability due to environmental change: concepts, issues, methods and case studies, United Nations Environment Program (UNEP)

Warner RM (2012) Applied statistics: from bivariate through multivariate techniques: from bivariate through multivariate techniques, Sage

WHO (2004) Guidelines for drinking water quality. 1, Recommendations

Winkel L, Berg M, Amini M, Hug SJ, Johnson CA (2008) Predicting groundwater arsenic contamination in Southeast Asia from surface parameters. Nat Geosci 1(8):536–542

Wisner B (2004) At risk: natural hazards, people's vulnerability and disasters. Psychology Press, New York